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Weighted Fusion of Pre-processing Techniques for Neural Network-based Image Haze Removal

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Abstract: Haze is the natural phenomenon, which affects an image's air light and visibility. It creates a layer that hides the information in an acquired hazy image and decreases its visibility. Hazy scenarios are mostly seen in the transportation sector and remote sensing. It affects the quality of an image captured. Haze is one of the major hurdles in several computer vision applications. This paper observes and analyses different methods of haze removal via image enhancement techniques. Proposes the weighted average of the image enhancement methods to generate the enhanced hazy input image as the initial step. These enhanced images do train the neural network to estimate transmission map as well as atmospheric light, used for haze removal from images. The proposed method is experimented with 135 hazy images from three standard datasets, alias I-Haze, NH-Haze, and O-Haze (45 images from each total 135 hazy images). It gives clearer results than a few similar existing haze removal techniques. Also, the experimental results tested with performance metrics Entropy PSNR, and SSIM have demonstrated the effectiveness of the proposed haze removal method having weighted fusion of pre-processing techniques.

Keywords: Dehazing, Haze, Ai-light, Transmission Map, Image Fusion, White Balance, Contrast Enhancement, Gamma Correction, Histogram Equalization, Neural Network

1. Introduction

Nowadays, because of increasing air pollution, there is an increase in the amount of particulate matter in the atmosphere, alias water droplets, ash, dust, and smoke. Images captured in such conditions are often degraded. These images have poor visibility and less contrast. This is because the particles in air cause absorption of light rays and scattering, resulting in a reduced quantity of light in the image. This phenomenon is called haze, and the images captured in such conditions are called hazy. When such images are used directly for computer vision algorithms, it drastically affects their performance [1]. Hence, dehazing becomes a necessary pre-processing step for these algorithms. Application areas of dehazing include remote sensing, satellite imaging, long-range imaging, intelligent transport systems, environment, landscape monitoring, etc.

Image dehazing algorithms use different computer vision techniques to process and retain important characteristics of it, alias scene statistics, color channels, image contrast, etc [2].

The haze removal method proposed here has two steps. The initial step is the weighted fusion of pre-processing methods applied to the hazy image, and the concluding step is haze removal using a neural network trained using the pre-processed images to estimate certain hazy image parameters. This paper presents a weighted fusion of White Balanced (WB), Gamma Corrected (GC), Contrast Enhanced (CE), and Histogram Equalized (HE) images derived from the hazy input image [3, 4]. Further, this fused image is fed to a neural network for dehazing purposes [5]. The experimental results are obtained using three standard datasets and are tested with image quality assessment metrics like PSNR, SSIM, and Entropy, whose results clearly showed that the fusion-based approach gives a much better output [6].

The key findings of the proposed work are presented below.

- Proposing the weighted fusion of enhanced hazy input images obtained from the pre-processing methods alias Histogram Equalization, White balancing, Gamma Correction, and Contrast enhancement. Three strategies of weighted fusion are proposed here

- Haze Removal using the atmospheric light, transmission map estimations done by a neural network trained using the weighted fusion of enhanced pre-processed hazy input images
- Experimental validation on three popular datasets, alias O-Haze, NH-Haze, and I-Haze explores the worth of the proposed haze removal method in various indoor/ outdoor/ non-homogeneous environments of hazy images.

The content outline of the paper is given herewith. The haze removal basics are put forth in Section 2. The proposed haze removal method is covered in Section 3. Section 4 demonstrates the experimentation environment set up. Section 5 indicates the objective and subjective results. The conclusion of the research is stated in section 6.

2. Literature Review

The haze removal problem is an actively researched area in image processing. In haze removal literature, various methods are proposed. They can be primarily Prior based or Data-Oriented techniques. Prior-based methods focus on hand-crafted image processing techniques that enhance an image's statistics, which encompasses techniques like Dark Channel Prior, Bright Color Channel Prior, and Color Attenuation Prior [7-9]. Data-Oriented methods are based on learning the haze-relevant features with neural networks and estimating natural characteristics. Some algorithms use image enhancement techniques, like White Balance and Contrast Enhancement, to enhance their outputs [3, 4].

In haze removal literature, haze formation is defined by the atmospheric scattering representation as given in equation 1. Let *H(s)* be the input hazy image and *J(s)* be the unhazed image. Let *t(s)* be the transmission matrix describing the camera's light, and A be the air-light observed from the image.

$$H(s) = J(s) * t(s) + A * (1 - t(s)) \qquad (1)$$

As the transmission matrix and air-light are unknown, most techniques try to predict those.

As the initial step, the proposed haze removal method does a fusion-based image enhancement. These enhanced hazy input images do train the neural network to predict the air-light and transmission map. After these estimations for an enhanced input hazy image, dehazing gets performed.

The estimation of air-light and transmission matrix is erroneous. Some methods capture the visual characteristics and estimate the air-light and transmission. However, in some cases, those estimations might be inaccurate where the air-light is similar to the scenario's colors [10, 11]. So instead of hand-crafted techniques, the learning-based Data-Oriented technique is used here. In the proposed method, the neural network estimates the transmission map and air-light from the hazy image fed to the network.

At first, multiple linear and nonlinear transformations, like Histogram Equalization, Gamma Correction, White Balance, and Contrast Enhancement, are applied to an image to manipulate the pixel values resulting in many intermittent enhanced versions of the hazy input image. Then a weighted fusion-based approach is used to fuse these intermittent images to obtain the enhanced hazy input image. After the enhancements, the input is fed to the neural network [5][12], which estimates the natural characteristics of the image, such as air-light *A* and transmission matrix *t(s)*. After estimating these characteristics, the unhazed image *J(s)* is obtained by equation 2. Let *H(s)* be a hazy input image

$$J(s) = \frac{H(s) - A * (1 - t(s))}{t(s)} \qquad (2)$$

The fusion of the prior-based and data-oriented approaches is an exciting area of exploration in haze removal. The proposed work of this paper attempts the combination of prior-based and data-oriented haze removal techniques to enhance the performance and the dehazed image quality.

The method proposed in [13] utilizes the learning-based approach of neural networks to predict the transmission matrix and the air-light and calculate dehazed images via equation 2. It poses an erroneous problem that can cause wrong estimation or low-quality dehazed results.

Multiple image enhancements such as White Balance, Contrast Enhancement, Gamma Correction, and Histogram Equalization are used to boost the image's visibility and decrease the haze in an image using a neural network [3, 4, 14].

Few of the haze removal attempts are specifically made for the night time images in recent research attempts [15, 16]

3. Proposed Method

The learning model-based dehazing techniques use a neural network to predict air light and transmission matrix. Hence, they largely depend upon the training dataset for the method to turn effective. These methods work well for particular indoor, outdoor, daytime, and night-time scenarios, but their results are not accurate when tested for different scenarios. e.g., a method trained for daytime conditions would give poor results when tested for hazy images with night-time scenarios. Enhancement-based methods apply certain image enhancement techniques to the hazy input image to remove unwanted artifacts and enhance the desired features. The proposed system uses image enhancement and also learning-based approaches as shown in figure 1.

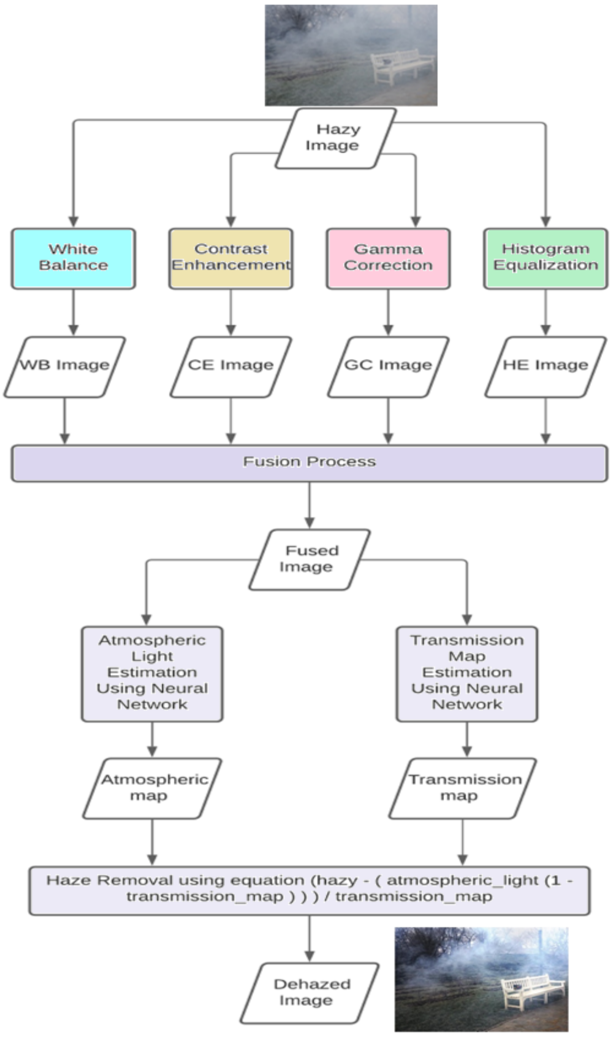


Figure 1. Block diagram of proposed weighted fusion of pre-processing techniques for neural network-based Image Haze Removal

Algorithmic steps of proposed model can be listed as follows

Step 1:	Read Input Hazy Image
Step 2:	Perform Preprocessing on input hazy image as A. Adjust White Balance to get WB Image B. Apply Contrast Enhancement to get CE Image C. Apply Gamma Correction to get CG Image D. Apply Histogram Equalization to get HE image
Step 3:	Get Fused Image by applying fusion on obtained WB Image, CE, Image, CG Image, and HE image
Step 4:	Estimate Atmospheric Light from Fused Image using Neural Network to get Atmospheric map
Step 5:	Estimate the transmission map from the Fused image using Neural Network
Step 6:	Get dehazing done using the estimated atmospheric and transmission maps by removing haze from the fused image
Step 7:	Get the final Dehazed Image as output

The reason is that enhancement-based techniques help the neural network better estimate the air-light and transmission map, further increasing visibility and giving better perception.

3.1 Image enhancement techniques used

Here, in the proposed method, a few of the pre-processing techniques are used to get the hazy input image enhanced.

3.1.1 White Balance

The first enhancement is the White Balanced image which aims to neutralize the colors in a hazy image [3]. Here, the Gray World White Balancing method [3] is used. It yields better results than most complex methods. It assumes that, with an adequate amount of color variation, the mean of each of the blue, green, and red channels should average out to the common grey value. It neutralizes the colors to their assumed common grey value.

Let *avg_blue, avg_green*, and *avg_red* be the mean values of the input image's Blue, Green, and Red color planes, respectively. Let *R_channel, G_channel,* and *B_channel* be the white balanced output of the input image color planes as given in equations 4, 5, and 6, respectively.

$$Total\_value = \frac{avg\_red + avg\_green + avg\_blue}{3} \quad (3)$$

$$R\_channel = \frac{Red * Total\_value}{(avg\_red + 0.001)} \quad (4)$$

$$G\_channel = \frac{Green * Total\_value}{(avg\_green + 0.001)} \quad (5)$$

$$B\_channel = \frac{Blue * Total\_value}{(avg\_blue + 0.001)} \quad (6)$$

3.1.2 Contrast Enhancement

The contrast-enhanced image is calculated by using a linear transformation [4][17]. Here, the average intensity $\hat{I}$ is subtracted from hazy input image *I* and multiplied with factor *μ* as shown in equation 7.

$$I_{CE} = \mu * (I - \hat{I}), \ Here\ \mu = 2 * (0.5 - \hat{I}) \quad (7)$$

Contrast Enhancement improves the visibility of the image linearly. But due to the linear nature of transformation, the darker regions tend to get even darker.

3.1.3 Gamma Correction

To reduce the limitations of the Contrast Enhancement, a nonlinear gamma correction transformation is used, as shown in equation 8. It amends the tristimulus values of image as per the human eye's perception. Here, *α = 1* and *γ = 2.5* are taken to enhance the image.

$$I_{GC} = \alpha * I^{\gamma} \quad (8)$$

3.1.4 Histogram Equalization

This method is used for adjusting the contrast of an image. It does this by using the distribution of frequent intensities, i.e., by stretching out an image's histogram. With the help of Probability Mass Function and Cumulative Distributive Function, the intensity values of the image are stretched out to improve visibility.

After computing all the enhancements individually on the hazy input image, the intermittent enhanced images are obtained. A weighted fusion process is applied to these intermittent enhanced images. A total of three combinations of the weighted fusion are proposed in this work as follows.

- 50% HE, 35% GC, 15% CE.
- 33% WB, 34% GC, 33% CE.
- 10% WB, 35% GC, 25% CE, 30% HE.

Where HE - Histogram Equalization,

GC - Gamma Correction,

CE - Contrast Enhancement,

WB - White Balance.

3.2 Estimation of parameters for haze removal using Neural Network [6]

The three proposed weighted fusion combinations produce three enhanced hazy input images fused according to the weights. These images are further passed as input to a neural network[5], which then estimates the air-light and transmission matrix. Once the parameters are estimated, the proposed method uses equation 2 for the dehazing of the input image. This is done for three hazy image datasets, namely O-Haze, NH-Haze, and I-Haze.

3.2.1. Atmospheric estimation using Neural Network

The proposed method considers that air-light is consistent all through the image. Hence, the predicted atmospheric map has a constant value for each pixel, and it is of a similar size as that of the input image given to the network. An 8-block U-Net structure with four convolutional blocks and four de-convolutional blocks, as suggested in [5], is used to adapt to it.

3.2.2 Transmission map Estimation

Here, a multi-scaled and fully connected encoder-decoder structure of CNN is used, as noted in [5]. The densely connected pyramid blocks with downsampling of CNN can refine the features extracted from CNN and improve the network's learning. At the end of the encoder, the sample size is 1/32 of the original. In the decoder up-sampling, dense blocks are used to restore the sample to its original size.

3.2.3 Image Dehazing

To join the relation between Air-light *A*, Transmission Matrix *t(s)*, and dehazed image *J(s)* from equation 2, it is embedded into the network [5]. The network performs the estimation and internally bridges the relationship between equation 2 elements.

4. Results

Three datasets, namely I-Haze, NH-Haze, and O-Haze, are used to validate the proposed haze removal method's results. Figures 2, 3, and 4 give a few examples from the I-Haze, NH-Haze, and O-Haze datasets. A total of 135 hazy images (45 from each dataset) are taken for experimental validation.

Three performance metrics alias Structural Similarity (SSIM)[6], Peak Signal to Noise Ratio (PSNR), and Entropy. PSNR and SSIM indicate the quality of the image compared to the reference image, while Entropy is a no-reference quality evaluator. PSNR and SSIM both require a clear reference to evaluate the quality. PSNR is the ratio of peak signal to mean square error in the image.

The minimum PSNR value is 0, and the maximum is 100. The more the value, the superior is the quality of an image. SSIM is based on three components of an image: luminance, contrast, and structure. Minimum and Maximum scores of SSIM are -1 and 1. The more the score of SSIM, the better the quality. Entropy is a reference less quality evaluator, calculated as the negative logarithm of probability mass function as equation 9. Here, let N be the count of grayscale levels (for 8-bit images: 256), P_i be the probability of a pixel with grayscale level i, and b be the base of the logarithm.

$$Entropy = -\sum_{i=0}^{N-1}[P_i * \log_b(P_i)] \qquad (9)$$

The next section covers the experimental results of the proposed technique. The implementation of the proposed technique is performed using Python and the hazy images of the O-Haze[19], NH-Haze [20], and I-Haze[18] datasets (45 images from each of the datasets, resulting in a total of 135 images) and their objective and subjective results are shown. In the case of objective comparison, the evaluation of dehazing outcomes is done using performance metrics like SSIM, PSNR, and Entropy scores.

Here, Figure 5, 6, and 7 show the dehazed output of the fusion-based approach on the I-Haze, NH-Haze, and O-Haze datasets. Figure 8 is the visual comparison of the fusion-based approaches with some neural network-based dehazing methods.

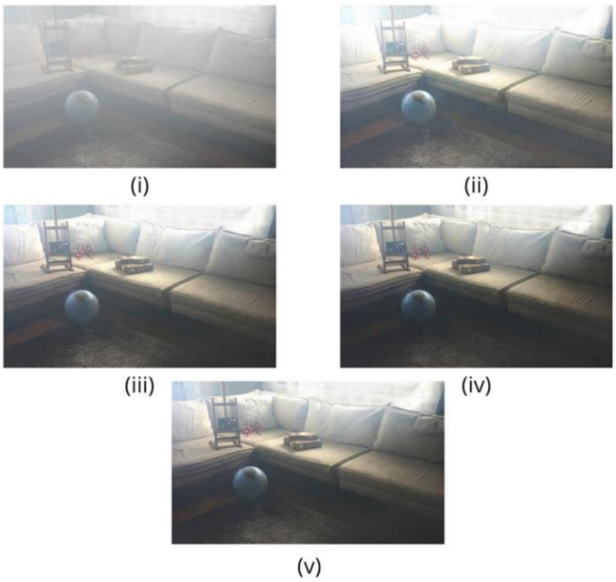
Tables 3, 1, and 2 represent the SSIM, PSNR, and Entropy results of the fusion-based approaches on NH-Haze, I-Haze, and O-Haze datasets. The quality comparison of the proposed method with PSNR, SSIM, and Entropy for O-Haze and NH-Haze with examples is shown in Tables 2, 3, and 1, respectively. The greater the scores, the superior the quality of the images. The results indicate that the proposed method, which uses fusion along with the neural network, gives better output than the case in which only the neural network was used.

The quality assessment parameters such as PSNR, SSIM, and Entropy are used for objective comparison. The methods are tested on multiple datasets, which include O-Haze, NH-Haze, and I-Haze, to include multiple scenarios like outdoor and indoor scenes for testing.

Figure 2. Images from I-Haze [18] benchmark dataset containing Indoor

Figure 3. Images from O-Haze [19] benchmark dataset containing Outdoor imagesimages

Figure 4. Images from NH-Haze [20] benchmark dataset containing Non-Homogeneous

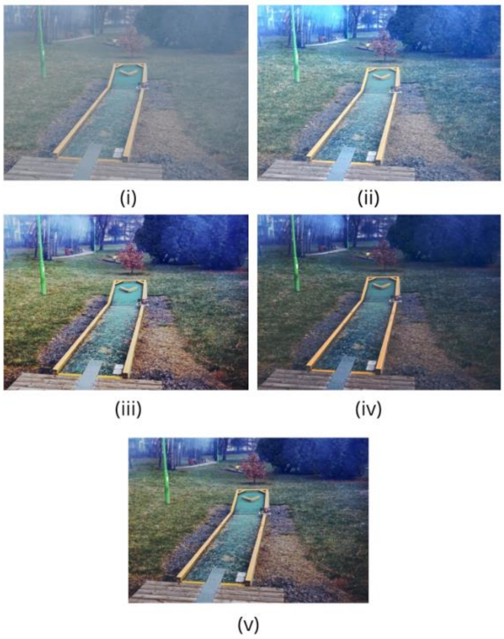


(i) Hazy Input Image, (ii) Neural Network [5], (iii) Proposed 50% HE, 35% GC, 15% CE + Neural Network (iv) Proposed 33% WB, 33% CE, 34% GC + Neural Network, (v) Proposed 10% WB, 25% CE, 35% GC, 30% HE + Neural Network

Figure 5. Results of the proposed algorithm on I-Haze [18] Dataset (HE - Histogram Equalization, GC - Gamma Correction, CE - Contrast Enhancement, WB - White Balance)

Table 1. Average values of PSNR, SSIM, and Entropy for I-Haze[18] Dataset (35 images) (HE - Histogram Equalization, GC - Gamma Correction, CE - Contrast Enhancement, WB - White Balance)

Image	Input Image (Hazy)	Neural Network-based haze removal [5]	Proposed haze removal with 50% HE, 35% GC, 15% CE + Neural Network	Proposed haze removal with 33% WB, 33% CE, 34% GC + Neural Network	Proposed haze removal with 10% WB, 25% CE, 35% GC, 30% HE+ Neural Network
PSNR	14.3105	14.8177	16.1760	16.2354	**16.8363**
SSIM	0.7127	0.7470	0.7560	0.7495	**0.7647**
Entropy	6.8667	7.2465	**7.4493**	6.8821	7.2660



(i) Hazy Input Image, (ii) Neural Network[5], (iii) Proposed 50% HE, 35% GC, 15% CE + Neural Network (iv) Proposed 33% WB, 33% CE, 34% GC + Neural Network, (v) Proposed 10% WB, 25% CE, 35% GC, 30% HE + Neural Network

Figure 6. Results of the proposed method on O-Haze[19] Dataset (HE - Histogram Equalization, GC - Gamma Correction, CE - Contrast Enhancement, WB - White Balance)

Table 2. Average scores of PSNR, SSIM, and Entropy for O-Haze[19] Dataset (45 images)

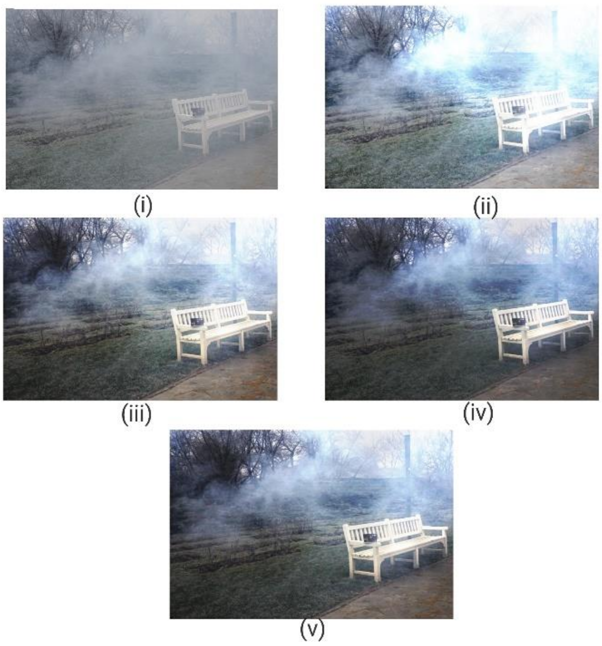
(HE - Histogram Equalization, GC - Gamma Correction, CE - Contrast Enhancement, WB - White Balance)

Image	Input Image (Hazy)	Neural Network-based haze removal[5]	Proposed haze removal with 50% HE, 35% GC, 15% CE + Neural Network	Proposed haze removal with 33% WB, 33% CE, 34% GC + Neural Network	Proposed haze removal with 10% WB, 25% CE, 35% GC, 30% HE+ Neural Network

PSNR	13.8083	11.1978	14.0114	**15.8675**	15.2698
SSIM	0.6170	0.6610	0.6932	0.6738	**0.7023**
Entropy	6.5348	7.1974	**7.5641**	7.0202	7.3853

Table 3. Average values of PSNR, SSIM, and Entropy for NH-Haze[20] Dataset (45 images)
(HE - Histogram Equalization, GC - Gamma Correction, CE - Contrast Enhancement, WB - White Balance)

Image	Input Image (Hazy)	Neural Network-based haze removal [5]	Proposed haze removal with 50% HE, 35% GC, 15% CE + Neural Network	Proposed haze removal with 33% WB, 33% CE, 34% GC + Neural Network	Proposed haze removal with 10% WB, 25% CE, 35% GC, 30% HE+ Neural Network
PSNR	11.6180	9.5555	11.3049	12.1768	11.8046
SSIM	0.4691	0.5226	0.5391	0.4970	0.5256
Entropy	6.8222	7.2321	7.6209	7.2778	7.5056



(i) Hazy Input Image, (ii) Neural Network[5], (iii) Proposed 50% HE, 35% GC, 15% CE + Neural Network, (iv) Proposed 33% WB, 33% CE, 34% GC + Neural Network, (v) Proposed 10% WB, 25% CE, 35% GC, 30% HE + Neural Network

Figure 7. Results of the proposed technique on NH-Haze[20] Dataset (HE - Histogram Equalization, GC - Gamma Correction, CE - Contrast Enhancement, WB - White Balance)

Table 4. Average values of SSIM and PSNR for NH-Haze, O-Haze, and I-Haze Datasets for fusion-based approach and state-of-the-art techniques

Dataset	Input Image (Hazy)		Zhang et al.[5]		Li et al.[21]		Cai et al.[22]		Fusion1 + Neural Net.		Fusion2 + Neural Net.		Fusion3 + Neural Net.	
	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR
O-Haze	0.617	13.808	0.661	14.011	0.591	15.371	0.687	14.345	0.693	14.011	0.674	**15.868**	**0.702**	15.269

I-Haze	0.713	14.311	0.747	12.818	0.725	15.053	0.619	13.884	0.756	16.176	0.749	16.235	**0.765**	**16.836**
NH-Haze	0.469	11.6	0.523	9.556	0.473	**12.245**	0.457	11.721	**0.539**	11.305	0.497	12.177	0.526	11.805

Table 5. Average values of Entropy for O-Haze, NH-Haze, and I-Haze, Datasets for fusion-based approach and state-of-the-art techniques

Dataset	Input Image (Hazy)	Zhang et al.[5]	Li et al.[21]	Cai et al.[22]	Fusion1 + Neural Net.	Fusion2 + Neural Net.	Fusion3 + Neural Net.
	ENTROPY	ENTROPY	ENTROPY	ENTROPY	ENTROPY	ENTROPY	ENTROPY
O-Haze	6.5348	7.1974	6.6724	6.5167	**7.5641**	7.0202	7.3853
I-Haze	6.8667	7.2465	6.9997	6.8628	**7.4493**	6.8821	7.266
NH-Haze	6.8222	7.2321	6.9724	6.8077	**7.6209**	7.2778	7.5056

Fusion1 = 50% Histogram Equalization, 35% Gamma Correction, 15% Contrast Enhancement.
Fusion2 = 34% Gamma Correction, 33% Contrast Enhancement, 33% White Balance.
Fusion3 = 35% Gamma Correction, 30% Histogram Equalization, 25% Contrast Enhancement, 10% White Balance.

Figure 8. Subjective comparison of proposed fusion-based method with existing state-of-the-art techniques

5. Discussion

The objective comparison of the fusion-based approaches with some neural network-based methods is shown in Tables 4 and 5. Figure 8 is the subjective comparison of the fusion-based method with some existing haze removal methods [5, 21, 22].

The objective and subjective comparisons show that the fusion-based approaches give greater SSIM, PSNR, and Entropy over other appropriate existing techniques. The subjective comparison recapitulates that the fusion-based method is superior at dehazing a multi-layer haze from the image. The problems of Oversaturation, Color Casting, and Low Visibility problems are reduced in the proposed fusion dehazing with the neural network method.

The future scope of the proposed work can be the use of other earlier presented pre-processing methods [23-26] for enhancing the quality of hazy input images before getting them used to train the neural network for haze removal.

6. Conclusion and Future Work

The paper recommends a fusion-based haze removal approach, which uses both enhancement-based and physical model restoration methods. A hazy input image is provided as input to White Balance (WB), Gamma Correction(GC), Contrast Enhancement(CE), and Histogram Equalization(HE) algorithms separately to get intermittent enhanced images. The output of these methods is fused in proposed proportions to recuperate details from the hazy input image. This output is provided as input to a neural network to approximate the parameters like air-light and transmission map. Later, the atmospheric scattering model dehazes the image. The experimental results obtained on three datasets, O-Haze, NH-Haze, and I-Haze, are tested with standard image quality assessment metrics like Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Entropy, whose results clearly showed that the fusion-based approach offers much superior output over the existing algorithms. The result of the fusion-based approach is used to remove multi-layered haze to preserve the scene's natural color and improve the image's quality. Extended work on haze removal may include faster haze removal algorithms and dehazing both daytime and night-time scenes and can be applied in different fields. The proposed method may be further explored in medical domain datasets for enhancement of the medical diagnosis images.

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Authors Contribution Statement

Sudeep D. Thepade: Conceptualization, Implementation and Result Analysis; **Kamal Shah**: Exploration and Result Analysis; **Satpalsing Rajput**: Drafting and Formatting with Presentation of Results; **A.A. Patil**: Experimental Explorations and Results Findings on O Haze Dataset; **C.M. Nawale**: Experimental Explorations and Results Findings on I Haze Dataset; **C.D. Taralkar**: Experimental Explorations and Results Findings on NH Haze dataset; **M.V. Suryavanshi**: Combining the results findings for all three datasets for the analysis. All the authors read and approved the final version of the manuscript.

Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

Data will be provided upon request.

Has this article screened for similarity?

Yes